A Wavelet- and Fourier-Based Estimation Scheme for Improved Blood Oxygenation Level Dependent (BOLD) Constrast Detection in Motion-Degraded fMRI

I. Atkinson[1], F. Kamalabadi[1], D. L. Jones[1], A. Nemani[2], K. Thulborn[2]

[1]Coorinated Science Laboratory and Department of Electrical and Computer Engineering, University of Illinois at Urbana-Champaign, Urbana, IL, United States,
[2]Center for Magnetic Resonance Research, University of Illinois at Chicago, Chicago, IL, United States

Introduction

The detection of blood oxygenation level dependent (BOLD) contrast to produce activation maps by fMRI is signal-to-noise ratio (SNR) limited. The BOLD signal change is usually only a few percent of the total signal and is often indistinguishable from the background variance without signal averaging. Detection requires statistical processing from many images acquired under each cognitive condition to be compared. The strategies used for this application span the full range of statistical tools without any universally accepted approach. The desire to improve signal detection has led to development of higher field magnets (e.g. 3.0 Tesla clinical scanners), improved quality assurance specifications of scanners, and more refined cognitive paradigms. The need for improved post-processing algorithms remains evident and is the motivation for testing the combined wavelet- and Fourier-based technique discussed below.

Data Processing Description

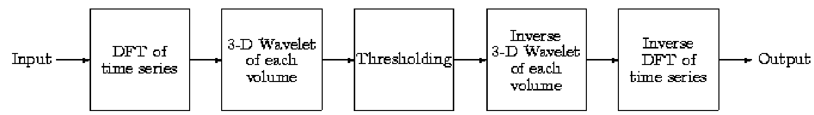

Figure 1: Block diagram of estimation scheme prior to statistical processing

Signal estimation is one method that can improve the SNR of a noisy signal. Optimal linear estimation (in terms of mean-square-error) of a signal from a noisy observation is achieved by the widely known Wiener filter. The Wiener filter uses second-order statistics to optimally decorrelate the data by transforming it into the Karhunen-Loeve (KL) domain. Once transformed, signal and noise are easily discerned, which allows noise to be attenuated while minimally distorting the signal. Although the results provided by the Wiener filter are mathematically desirable, use of this optimal estimator is often impractical, as its computation requires second-order statistics of the signal, which are generally unknown, and the inversion of a large matrix.

When applied to an fMRI dataset, the Wiener filter optimally decorrelates the signal in both three-dimensional (3-D) space and time. This spatial-temporal decorrelation is key to the performance of the Wiener filter, as the true signal will be compacted into a few significant coefficients while the noise will remain in the vast majority of the coefficients. We have used a wavelet- and Fourier-based approximation to the Wiener filter for near-optimal estimation of fRMI data from a block paradigm experiment. This scheme approximately decorrelates the data using a discrete Fourier transform (DFT) to decorrelate temporally and a 3-D discrete wavelet transform (DWT) to decorrelate spatially. The approximately decorrelated coefficients are then denoised using a thresholding operator that suppresses coefficients likely due to noise and retains coefficients likely due to signal. Finally, the denoised coefficients are recorrelated using an inverse 3-D DWT and inverse DFT. A similar technique has been applied to multichannel image estimation and was shown to provide impressive SNR gains [1]. A block diagram of the proposed estimation algorithm is shown in Figure 1. Note that unlike the Wiener filter, this estimation scheme requires no signal statistics or computationally costly matrix inversion. In addition, by utilizing fast forms of the discrete Fourier transform (DFT) and discrete wavelet transform (DWT), the proposed algorithm can be implemented in a highly efficient manner.

Since the data is from a repetitive block experiment, the activation of a single voxel will be periodic, and therefore the DFT will compact the temporal signal well. Furthermore, it is well known that a wavelet basis forms an approximate KL basis for a wide class of signals, which means the 3-D DWT should provide good spatial decorrelation for many signals. The combined effect of the DFT and 3-D DWT is decorrelation of the signal in both time and space that rivals that of the Wiener filter, but without the need for second order-signal statistics. A wide variety of thresholding operators may be used to denoise the decorrelated coefficients. While one could use a simple hard or soft threshold to provide basic denoising, it is also possible to use a more sophisticated threshold that incorporates *a priori* information, such as activation frequency, into the threshold decision. The results shown below use a soft (shrinkage) threshold.

Methods

Functional MRI was performed at 3.0 Tesla on a whole-body long-bore scanner (Signa, General Electric Medical Systems, Milwaukee, WI) using a standard, single-channel, quadrature head coil. Acquisition was performed using gradient-echo, echo-planar imaging (Rtip, TR = 3000ms, TE = 30ms, matrix = 128x128, 22 slices, 100 volumes). In order to see the effect of the estimation scheme, the data shown were selected as being inferior to an optimal dataset due to increased (>0.3 voxel) head motion. The paradigm consisted of a block design of alternating right hand opening and closing (1Hz, 30s) with left hand opening and closing (1Hz, 30s). Instructions were presented visually using an MRI-compatible synchronization control system (MRIx Technologies, Bannockburn, IL). The time series of images was processed using an unpaired, two-tailed, student t-test (activation map shown with positive side of t-test in red, negative side of t-test in blue) before and after performing the combined wavelet and Fourier estimation algorithm described above. The detection threshold for activation, defined as the statistical threshold at which the false positive (Type 1 error) and false negative (Type 2 error) error rates are equal and at the 95% confidence level, was calculated before and after the application of the estimation scheme. The error rates were estimated using Monte Carlo simulations of the randomized time courses of all voxels in the images in which discrete known signal increments were systematically added in the same block design as the paradigm.

Results

The representative results of activation maps before and after the estimation procedure are shown in Figure 2 and 3, respectively. The estimation scheme shows a more robust map in terms of volume of activation in the primary motor cortex (shown) and in the cerebellum (not shown). The detection threshold was decreased by a factor of greater than two by using the estimation algorithm. Specifically, the estimation scheme increased the confidence limit for the detection threshold of a 1% signal change from 89% to 96%, which is reflected as a removal of the noisy background in Figure 2. However, the supplementary motor areas that are always observed along the medial frontal lobes area in a good dataset were not detected before or after application of the estimation scheme. Thus, not all expected activation was recovered from these inferior quality datasets with this algorithm.

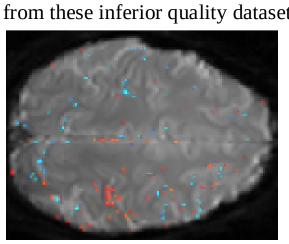

Figure 2. Activation map prior to using the estimation scheme. Student t-test shows considerable noise throughout both hemispheres of comparable significance to the expected activation in motor cortex.

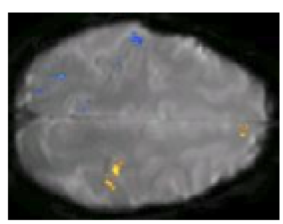

Figure 3. Activation map after using the estimation scheme. Student t-test shows activation in the primary motor cortex with reduced noise compared to Figure 2. Activation in the anterior left frontal lobe and right parietal lobe are not expected and represent false positive activation within the confidence limits set by the threshold.

Discussion

The estimator improves detection of activation in motion-degraded data. Specifically, the detection threshold (at which Type I and Type II errors are set to be equal) was decreased by a factor greater than two, which has been quantified through simulations as being an improvement in confidence limit (for the detection threshold of a 1% signal change) from 89% to 96%. Such estimators warrant further investigation.

References

[1] I. Atkinson, F. Kamalabadi, S. Mohan, and D. L. Jones, “Wavelet-Based 2-D Multichannel Signal Estimation.” Proceedings of IEEE International Conference on Image Processing, 2003.

Acknowledgments

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